

# Stress analysis using ECG and Respiratory Signals of Automobile Drivers by Pan Tompkins Algorithm

C. Jaya Suriya<sup>1</sup>, J Jeya Christy Bindhu Sheeba<sup>2</sup>

<sup>1</sup>Assistant Professor, Department of ECE, PET Engineering College.

<sup>2</sup>PG Scholar, Department of ECE, PET Engineering College.

**Abstract-** This paper deals with the physiological signal variations of a person with their respective stress. It was analyzed by the ECG and respiratory signals received from the automobile drivers who used to drive on different road conditions to obtain various stress levels. First part is to extract two feature signals from the physiological signals and the extracted feature signals are QRS power spectrum and the breathing rate. The feature signal variation with the respective stress was expressed in terms of correlation coefficients and was tabulated. The analysis demonstrates the variations in the reference signals with respect to the stress of the driver. The better feature signal to analyze the stress is the QRS power signal as it clearly shows more correlation with the heart rate marker signal. The analysis concludes that the stress monitoring can be done by using the physiological signals as a factor.

**Keywords**—Stress, QRS power, ECG, breathing rate, respiratory signal and correlation coefficient.

## I.INTRODUCTION

### STRESS

The reaction of human being based on their physical and mental changes according to the events and situation is known as stress. Stress is experienced by the people in different ways and for different reasons. Stress in extreme level causes severe health issues such as cardiovascular problems. It also affects the central nervous system. The more familiar form of stress is feeling distressed, oppressed and out of control. Stress can affect the thoughts, feelings, behavior and the body conditions. It also produces sleeping problems, sweating, loss of appetite and lack of concentration. The drivers must require full concentration and a calm attitude. Stressed and strong emotions result from the driving or other un related matters can affect a driver's abilities. For example, research as shown that angry drivers are more likely to take perils such as speeding, rapidly switching lanes, tailgating and jumping red lights. [1]

*Manuscript received Oct 15, 2015.*

C. Jaya Suriya,, Electronics and Communication Engineering Anna University/PET Engineering College

J Jeya Christy Bindhu Sheeba ,Electronics and Communication Engineering, Anna UniversityPET EngineeringCollege

Every driver is prone to stressful conditions even if they do not have stress in their daily life. Traffic jams, tailgating and generally dealing with other drivers risk-taking can all lead to heightened stress levels. If a person handles a vehicle while in stressed condition they run a much greater risk of being involved in a crash that kills or injures them or to another road user. The factors associated with an increased risk of collisions are feeling rushed and lower life satisfaction as stated by UK's Health and Safety Executive (HSE) research. [2]

### EFFECTS OF STRESS

The reaction of the body to any stimuli which disturbs its equilibrium is stress. The alteration in the equilibrium by various hormones results in destructive immune system. Research shows that stress has negative effect on the immune system. This is done by subjecting the participants to variety of viruses. The immune system is affected by stress in many ways.

The physiological signals are as follows Respiratory (RSP) signal, Electrocardiogram (ECG) signal, Electroencephalogram (EEG) signal, Electromyography (EMG), blood volume pulse (BVP), Skin temperature (SKT), Skin Conductivity Electro-Dermal Activation (EDA), and GSR galvanic skin response. These traditional physiological signals are used in emotion recognition. The endocrine system and the autonomic nervous system dominate the physiological variations, so it is not dominated by the subjective conscious control.

More objective and real data can be obtained by the physiological signal analysis method. Some characteristic or the combination of the characteristics with respective specific emotion was observed. The harmonious human-machine affective interaction is achieved by using these characteristics

for the emotion recognition. Considering the complexity and effectiveness of collecting all physiological signal only two kinds of physiological signals: RSP signal and ECG signal is preferred to recognize the emotion.

## ELECTROCARDIOGRAM

The elucidation of the electrical activity of the heart over some period of time which is detected by electrodes attached to the surface of the skin over certain time period is known as Electrocardiography and is recorded by a device known as Electrocardiogram. The heart's electrical conduction system is measured by an ECG. It is done by collecting the impulses which are generated by the action of polarization and depolarization of cardiac tissue and is translated into a waveform. This waveform shows the heartbeat's rate and regularity, chambers size and position and detects the damage in the heart. The backbone of cardiology is the Electrocardiogram (ECG). The rise in ECG is produced by the graphical tracing of depolarization and repolarization activities produced by the heart and can be measured by placing an array of 12 different electrodes placed on the body surface of a patient. In order to monitor any abnormal cardiac rhythm that cannot be observed by normal ECG test is performed by monitoring ECG signals from one or two leads.

A series of repetitive waves namely P-QRS-T represents the typical tracing as shown in Fig.1 and electrical activity is indicated by U waves that arises from isoelectric line. Each wave has an important relation with the heart, depolarization of atria is represented by P wave, ventricular depolarization is given by QRS complex and ventricular repolarization is associated with T-wave. Life threatening disturbances in the intervals, amplitudes and areas of these waves are recorded from the surface electrocardiogram.

The most prominent feature in electrocardiogram is the QRS complex because of its specific shape and is considered as the reference wave in ECG feature extraction. The useful tools in analyzing ECG feature is QRS peak detectors. The activity of the heart is reflected by the periodic signal ECG. the normal and pathological physiology of heart can be

obtained from ECG. It is very difficult to view visually the ECG signals being non-stationary in nature.

The condition of the heart of a patient is a important information and is given by the Electrocardiogram (ECG). For instance, ECG recorded from a patient with heart disease often exhibits abnormal characteristic waves. Automatic analysis and classification of ECG can ease the burden of cardiologist and speed up the diagnosis. However, to develop an accurate system for automatic ECG diagnosis is not a trivial problem.

The wave which is on the first right known as the P wave and it is round in shape. The first wave denotes the arterial depolarization and it is not more than 0.1 sec. The QRS wave represents the ventricular depolarization it lasts for 0.04 to 0.12 seconds. In between the P and the QRS complex wave is the PR interval.

## II PROPOSED METHOD

### QRS DETECTION ALGORITHM

It is done by using Pan Tompkins Algorithm. The algorithm was implemented in the following way:

Input is given to band pass filter. The output of band pass filter is then given to squaring and then its output is given to integrator. The output of the integrator is the required output. Band pass filter was implemented by cascading one low pass filter with cut off frequency of 11Hz and a high pass filter with cut off frequency of 5 Hz. The high pass filter was implemented by using an all pass filter minus low pass filter. Then it introduces a delay of 5 samples. High pass filter also introduces a delay of 13 samples. This has to be compensated finally while extracting the QRS complex from the ECG signal.

Derivative filter functions in such a way that it will suppress the low frequency components such as P and T waves and it will enhance the high frequency QRS complex. The filter equation for the derivative operation is

$$y(n) = 1/8[2x(n) + x(n-1) - x(n-3) - 2x(n-4)]$$

Squaring operation is done to enhance the QRS complex by making the result positive and emphasizing large differences from QRS complex. It also suppresses the

P and T waves. The output of the derivative operator will count the number of peaks within the duration of a single QRS complex. Moving window integrator is used to smooth this output. The window width has to be selected in such a way that it should enclose the QRS complex only. If the window length is too small it produces multiple peaks, if it is large width it will enclose T wave also. In this paper a window width of 31 was used and got a good output.

Welch method is used to find the power estimation. The reason for choosing Welch method for power estimation is because it takes the average of the modified periodogram of the portioned segments of the signal so that the output of the Welch power spectrum will be a smoothed one. Hanning window of length 6 is used for the PSD calculation.

The equation for the correlation coefficient is:

$$C(x, y) = E \{ (X(n) - \bar{x})(y(n+k) - \bar{y}) \} / (\sigma_x \sigma_y) \quad (3.11)$$

Where

R= correlation coefficient

C (x, y) = Cross Covariance of x and y

= Standard deviation.

E { } = Expectation value

The respiratory signal is taken as the marker signal from which the values are taken by the expansion and contraction of the lungs during the process of breathing.

## II.RESULTS AND DISCUSSION

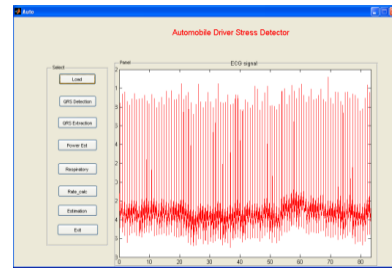


Fig 3.1 ECG signal

Fig 3.1 shows the ECG signal which is taken from the drivers for duration of ten seconds is obtained by using the GUI interface.

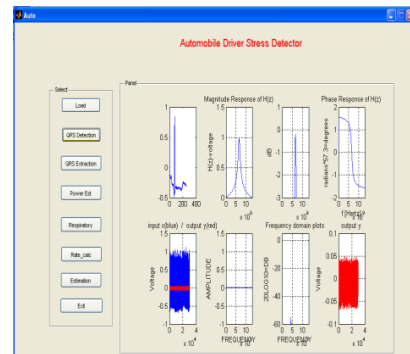


Fig 3.2 QRS detection

Here QRS detection is carried out in the input signal.

In the first section, it shows the single ECG signal with PQRST waves. The next is the reference signal which has a peak. The QRS signal is detected from the single ECG and the phase response of the acquired QRS signal obtained.

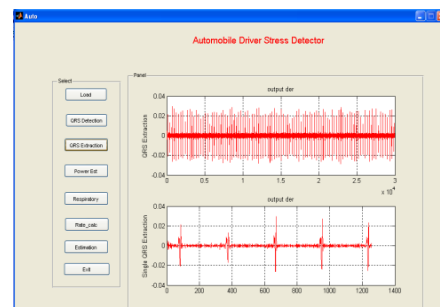


Fig 3.3 QRS extraction

Fig 3.3 shows the detected QRS signal extracted from the multiple QRS signals using the derivative filter. The extracted QRS signal for the duration of 1.4 seconds is obtained.

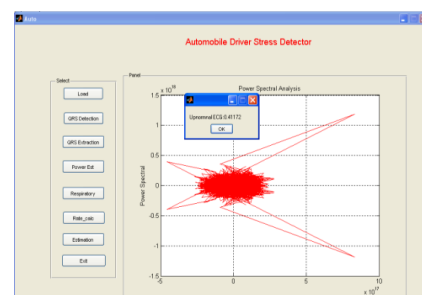


Fig 3.4 Power Estimation

Fig 5.4 shows the power estimation of the detected QRS signal. The power spectral density is given by the parseval's theorem of the fast Fourier transform.

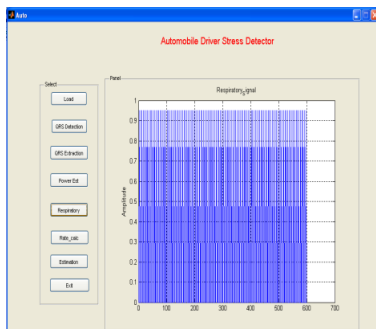


Fig 3.5 Respiratory Signal

Fig 5.5 shows the respiratory signal with time in the x-axis and the amplitude in the y-axis. It is recorded for about 0.06 seconds.

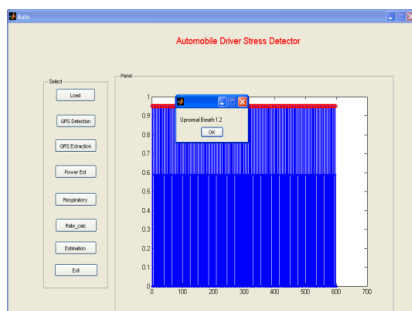


Fig 3.6 Rate Calculation

Fig 5.6 shows the rate calculation in the respiratory signal using the peak counter.

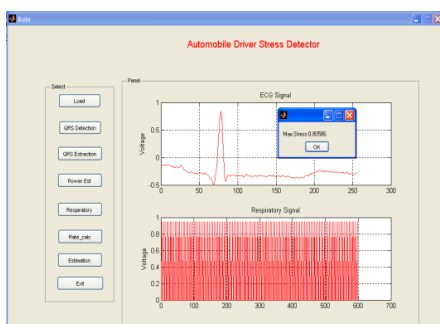


Fig 3.7 Stress Estimation

By comparing the power estimated in the QRS signal and the rate calculation of the respiratory signal, the stress of about 0.8 is obtained.

## CONCLUSION

The analysis done in this paper clearly proved the variation of physiological parameters with respect to the stress developed. Persons with stressful minds are very likely to have heart diseases since their ventricles take an extra

power to pump the blood and this will increase the blood pressure which will cause the problems of hypertension.

At present most of the people are affected by stress and it is good to perform practices which can reduce their stress which will make them healthy. Low-power physiological-signal recording technologies have emerged for advanced medical applications enabled by low-power devices. For many envisioned applications, however, it is critical to extract clinically valuable outputs from the acquired physiological signals. The challenge is that analyzing physiological signals requires high-order model due to the complex nature of the underlying processes, and patient-specific models are often needed since the manifestations of targeted states are highly variable. Machine learning offers promising tools to address both challenges, but the computations involved are not well handled by traditional DSP, and thus the high-order models required for accurate analysis dominate energy consumption. In this work, we propose a biomedical processor with configurable machine-learning accelerators for low-energy and real-time detection algorithms.

## FUTURE WORK

As a part of future research, it is possible to analyze other physiological signals which can give a higher metric for stress analysis. The comparison between different categories of subjects also will help to study about the stress in a better way. That can be used as a future aspect of the research. From the light of the research conducted for this paper, the overall conclusion is that, how much stress is reduced, that makes much healthier.

Two QRS detection methods are studied and compared. This result shows that the "So and Chan" algorithm gives better value. In some conditions, the detected T wave in the previous beat overlapped with the P wave in the current beat. In this stage, the P and T waves' information are not used in automatic ECG classification. Therefore, the autocorrelation approach to ECG classification is carried out using only the information of the QRS complex. The classification algorithm is trained to recognize four types of beat.

## REFERENCES

- [1] Chan K L, 1997, "Development of QRS detection method for real-time ambulatory cardiac monitor", Proc 19<sup>th</sup> Annu Int Conf IEEE EMBS, Chicago, USA, 289-292
- [2] A. Csavoy, G. Molnar, and T. Denison, "Creating support circuits for the nervous system: Considerations for "brain-machine" interfacing," in *Proc. IEEE Symp. VLSI Circuits*, Jun. 2009, pp. 4–7.
- [3] T. Denison, K. Consoer, W. Santa, A.-T. Avestruz, J. Cooley, and A. Kelly, "A 2 W 100 nV/rtHz chopper-stabilized instrumentation amplifier for chronic measurement of neural field potentials," *IEEE Solid-State Circuits*, vol. 42, no. 12, pp. 2934–2945, Dec. 2007.
- [4] Dharmawan, Z. 2007, "Analysis of Computer Games Player Stress Level Using EcG Data", Man-Machine Interaction Group, Delft University of Technology, Delft, Netherlands.
- [5] Friesen G M, Jannett T C, Jadallah M A, Yates S L, Quint S R and Nagle H T, 1990, "A comparison of the noise sensitivity of nine QRS detection algorithms", *IEEE Trans BME*, 37, 85- 98
- [6] Gritzali F, Frangakis G and Papakonstantinou G, 1989, "Detection of the P and T waves in an ECG", *Comput and Biomed Res*, 22, 83-91
- [7] Horlings, R. 2008, "Emotion recognition using brain activity", Man-Machine Interaction Group, Delft University of Technology, Delft, Netherlands.
- [8] Jennifer A. Healy and Rosalind W. Picard, "Detecting Stress During Real-World Driving Tasks Using Physiological Sensors," *IEEE Transactions on Intelligent Transportation systems*, vol. 6, no. 2, June 2005.
- [9] Jiapu Pan and Willis J. Tompkins, Real Time QRS Detection Algorithm," *IEEE Transactions on Bio Medical Engineering*, vol. BME-32, no. 3, March 1985.
- [10] Kim, N. Lu, R. Ghaffari, and J. A. Rogers, "Inorganic semiconductor Nanomaterials for flexible and stretchable bio-integrated Electronics," *Annu. Rev. Biomed. Eng.*, vol. 14, pp. 113–128, Aug.2012.
- [11] Lai K T and Chan K L, 1998, "Real-time classification of electrocardiogram based on fractal and correlation analyses", Proc 20<sup>th</sup> Annu Int Conf IEEE EMBS, Hong Kong, 119-122
- [12] Pan J and Tompkins W J, 1985, "A real- time QRS detection algorithm", *IEEE Trans BME*, 32,230-236
- [13] Rangaraj M. Rangayyan, "Bio Medical Signal Analysis – A Case Study Approach", 4th ed. IEEE press, 2009.
- [14] Ruha A, Sallinen S and Nissila S, 1997, "A real-time microprocessor QRS Detector system with a 1-ms timing accuracy for the measurement of Ambulatory HRV", *IEEE Trans BME*, 44, 159- 167
- [15] A. Shoeb and J. Guttag, "Application of machine learning to epileptic seizure detection," in *Proc. Int. Conf. Mach. Learn.*, Jun. 2010.
- [16] Soria-Olivas E, Martinez-Sober M, Calpe-Maravilla J, Guerrero-Martinez J F, Chorro-Gasco J and Espi-Lopez J, 1998, "Application of adaptive signal Processing for determining the limits of P and T waves in an ECG", *IEEE Trans BME*, 45, 1077-1080
- [17] Spelke, E.S., Dehaene, S. 1999, "Biological foundations of numerical thinking", *Trends in Cognitive Sciences*, 3, page 365- g366.
- [18] P. Suffczynski, S. Kalitzin, and F. H. L. da Silva, "Dynamics of nonconvulsive epileptic phenomena modeled by a bistable neuronal network," *Neuroscience*, vol. 126, no. 2, pp. 467–484, 2004
- [19] N. Verma, A. Shoeb, J. Bohorquez, J. Dawson, J. Guttag, and A. P. Chandrakasan, "A micropower ECG acquisition SoC with integrated feature extraction processor for a chronic seizure detection system," *IEEE J. Solid-State Circuits*, vol. 45, no. 4, pp. 804–816, Apr. 2010.
- [20] Vila-Sobrino J A, Regueiro C V and Sanchez E, 1998, "Classifying multichannel ECG patterns with an adaptive neural network", *IEEE EMBS Mag*, 45-55
- [21] P.D. Welch, "A Direct Digital Method of Power Spectrum Estimation", *IBM Journal*, April 1961.
- [22] K.J.W Wilson, Anne Waugh, Janet S. Ross, "Ross and Wilson Anatomy and Physiology in Health and Illness", 8th ed. Churchill Livingstone, 1996.



C Jaya Suriya received the B.E degree in Electronics and Communication Engineering from PSN College of Engineering, 20 and M.E degree from Noorul Islam College of Engineering, Kumarakoil. She is currently working as an Assistant Professor in Department of Electronics and Communication in PET Engineering

College, Vallioor. Her research areas include image processing, wireless communication systems, Analog and digital communication systems.



J Jeya Christy Bindhu Sheeba received the B.E degree in Electronics and Communication Engineering from Anna University, Chennai, and 2014. She is currently doing his Master of Engineering in Communication systems in PET Engineering College, Vallioor. Her areas of interests include Antennas Theory, Electromagnetics, Digital Image Processing and Wireless Systems.